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Innovative Decision and Forecasting Approach on Navigation Risk

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ABSTRACT In view to the unstable navigation risk assessment and make the future navigation risk forecasting, an innovative decision and forecasting approach is put forward in this study. Different from the existing literature, at the current time step, we first deduce an enhanced evidence combination rule to integrate uncertain and conflicting evidences by using weighted basic probabilistic assignment and matrix operation. As a result, a stable decision is effectively achieved no matter what characteristics of the available evidences are. Further, an improved α-β filter is designed with its adaptive coefficients in the novel filtering framework in order to forecast the future navigation risk. What's more, it is an excellent communication between the combined basic probabilistic assignment and the improved α-β filter for the first time. After the deep analysis of the computational complexity, a plenty of numeric simulations and actual experiments are provided to indicate the reliability and efficiency of the proposed approach.

INDEX TERMS Navigation risk, combination rule, decision, forecasting, computational complexity.

I. INTRODUCTION

Modern transportation has an important role in the advances of global trade and natural resources recently. As for maritime traffic accident and road traffic accident, the navigation risk represents the occurring probability of danger or safety [1], [2]. There are usually five levels of navigation risk in practical applications, that is, trivial level, tolerable level, moderate level, substantial level and intolerable level [3], [4]. The dangerous navigation mainly contains the latter two risk levels that fatally cause the unexpected personal disaster and property loss. Therefore, how to effectively assess the navigation risk has become a popular research topic in the academic circles.

Proceeding from the existing assessment methods of navigation risk, we can easily find that the analytic hierarchy process (AHP) is an important multi-evidence decision-making method [5]–[8]. In the field, [9] presented a ship integrated navigation system based on AHP in order to assess navigation risk. Aiming at both complexity and ambiguity, a risk assessment method based on the triangular fuzzy number AHP was proposed in [10]. According to the principle of system engineering, a fuzzy AHP was applied to calculate the weight for each index. In the comprehensive collection in the maritime accident database, [11] analyzed the navigation risk using the fuzzy AHP. Combined grey evaluation with AHP, a determination model was established for priority connectivity assessment value of each node, and the selection weights of road traffic network were obtained in [12]. Given that the discriminate matrix is very important in AHP, the matrix consistency must be continuously tested [13]. Therefore, [14] proposed an improved AHP to solve the problem of risk judgment matrix consistency. Inevitably, the defects of AHP lie in multi-evidence. Regarding on the available evidences, the Dempster-Shafer (D-S) evidence theory is a probabilistic appropriate combination method [15], which has been used in traffic applications without prior probabilities. For the basic probabilistic assignment (BPA), two alternative methods for combining multi-evidence were explored in [16]. First, an improved D-S evidence theory on safety risk perception was proposed in [17], where the combination rule and weighted rule were utilized to synthesize multi-evidence. Concerning on the waterways risk, a navigation assessment model based on D-S evidence theory was proposed in [18], which utilized the evidential reasoning and index level to merge BPA. Then, [19] embroidery complemented

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the risk analysis and helped the decision maker. We find that, by merging some interval-valued fuzzy sets, the D-S evidence theory provides the systematic decision support. In view to the interval fusion, an evidence combination rule was developed, and then fed into a fuzzy Bayesian network in [20]. Since the D-S evidence theory modeled by evidences cannot be directly combined, it cannot provide reliable decision and has low complexity based on uncertain and conflict evidences.

With the rapid development of modern science technology, the information forecasting emerges as the times require. The neural network, as a set of connected neurons, can receive heterogeneous signals and generate prediction. The back propagation is fundamental so that the back propagation neural network (BPNN) demonstrates what the correct result would be under multi-evidence. For this reason, [21] presented a risk decision system that contained the normalization of image size as well as the creation of risk characteristics. In BPNN, the computational complexity equals the product of the size of risk set and the number of nodes in hidden layers. Once the total number of required nodes is larger, the complexity will be higher. Aiming at running effectiveness, the α-β filter, on the other hand, can presume the complex system under a dynamic model and achieve the steady-state solution with exponentially-reduction calculation when the risk levels is small. Simultaneously, this filter is one of practical techniques solved in the iterative and decentralized manner [22]. For example, a new α-β filter was designed to the satisfactory results under the noisy condition in [23]. Afterwards, a fuzzy α-β filter for predicting maneuvering targets was presented in [24]. Therefore, it is our research enthusiasm that the BPNN can be replaced with the α-β filter to forecast navigation risk for avoiding potential danger. In this work, the combined BPA will be forecasted using the α-β filter. However, it is too difficult for the existing α-β filters to adaptively compute filtering gains of maneuvering BPA for accurate forecasting.

How can we establish an improved D-S evidence combination rule to make stable decision at the current time step using various evidences? How can we model a novel α-β filter to forecast the navigation risk for the next time step using combined BPA? To answer the double questions, an innovative detection and forecasting approach is proposed. The main innovations in the study, unlike the general assessment methods, are outlined as follows:

1) An enhanced evidence combination rule is explored to integrate uncertain and conflict evidences based on both weighted BPA and matrix operation with low computational complexity.

2) An improved α-β filter is utilized with the adaptive filtering coefficients, in the filtering framework, in order to forecast the future navigation risk and avoid navigation danger for the first time.

3) With respect to practical applications, the overall performance of the proposed decision and forecasting approach is discussed in maritime traffic and road traffic.

The organization of this study is assigned as follows: In Section 2, the related works on the D-S evidence theory is formulated. In Section 3, we propose the improvements of BPA computation and the BPA combination under the novel matrix operation. Afterwards, the optimal α-β filter is derived with its adaptive filtering coefficients for the maneuvering BPA. Further, the computational complexity is analyzed. In Section 4, the numerical study and associated experiment are discussed with prospective results to verify the decision and forecasting performance of the proposed approach. In the last section, we draw the conclusions, and then make the next research plan.

II. RELATED WORKS

Suppose that the different evidences in the D-S evidence theory are mutually exclusive in a space Θ, we have:

$$\begin{cases} \sum_{i\in\Theta} m_{ji} = 1, \quad 0 \le m_{ji} \le 1 \\ m_j(\varphi) = 0 \end{cases} \tag{1}$$

where $m_{ji} : 2^{\Theta} \to [0, 1]$ is the original mass function, and $i\,(i = 1, \cdots, s)$ is the navigation risk level.

As we know, the belief of the given evidence is given by the sum of BPAs, i.e., $\mathrm{Bel}(i) = \sum_{i\subseteq\Theta'} m_{j\Theta'}$, and the plausibility equals 1 minus the sum of BPAs. In general, the plausibility function is used when the current evidence is true, that is, $\mathrm{Pl}(i) = \sum_{i\cap\Theta'\neq\varphi} m_{j\Theta'}$. Then, the classic D-S evidence theory can provide an effective measure in the period $[\mathrm{Bel}(i), \mathrm{Pl}(i)]$. According to the classic evidence combination rule, the combined result of $j\,(j = 1, \cdots, n)$ raw BPAs related to the associated evidences is given by:

$$\begin{aligned} \tilde{m}_j &= m_{1i} \oplus m_{2i} \oplus \cdots \oplus m_{ji} \\ &= \frac{\sum_{\overset{s}{\underset{i=1}{\cap}} i\in\Theta} m_{ji}}{1 - \sum_{\substack{i,i'=1 \\ i\neq i'}}^{s} m_{ji}\tilde{m}_{(j-1)i'}} \end{aligned} \tag{2}$$

Aiming at the uncertain evidences in the actual navigation environment, the classic evidence combination rule may become invalid. At this time, the sum of all BPAs is less than 1, and then brings about unstable combination results to a certain extent. Therefore, the extra BPA φ_j of the uncertain navigation risk level is used to compensate the deficient component during the process of combination:

$$\begin{cases} \sum_{i=1}^{s} m_{ji} \le 1 \\ \varphi_j = 1 - \sum_{i=1}^{s} m_{ji} \end{cases} \tag{3}$$

Although φ_j represents the uncertain evidences in the navigation environment, the combination result has still error when m_{ji} takes 0.

Remark 1: The evidence combination rule in Equation (2) has high computational complexity when i and j are large. Besides, the decision is unstable when $m_{ji} = 0$. We will enhance the robustness of conflicting evidences and reduce the complexity in a new combination mechanism.

III. METHODOLOGY

A. BPA COMPUTATION

Given that the heterogeneous evidences in traffic engineering are not reliable because of their characteristics, we reduce the influence from the uncertain and conflicting evidences as far as possible for navigation risk assessment.

Let $C_j = \sum_{\substack{i,i'=1 \\ i \neq i'}}^{s} m_{ji}\tilde{m}_{(j-1)i'}$ in Equation (2) be the product of inconsistent BPA. We find that the value the higher, the conflict the higher. The relationship between the value and its conflict is defined by:

$$\begin{cases} \text{high conflict}, & 0.975 \leq C_j < 1 \\ \text{moderate conflict}, & 0.900 \leq C_j < 0.975 \\ \text{low conflict}, & 0 \leq C_j < 0.900 \end{cases} \tag{4}$$

Considering the uncertainty and conflict, we use the following probability to define the uncertainty and conflict of the associated evidences:

$$\mathrm{Bet}\left(\mathbf{m}_j\right) = \sum_{i \in \Theta} \frac{1}{s} \frac{m_{ji}}{\left(1-\varphi_j\right)} \tag{5}$$

where $\mathbf{m}_j$ is a BPA vector of m_{ji} in a given Θ and $\varphi_j \neq 1$. The degree on the BPA m_{ji} supported by other BPA $m_{j'i}$ $\left(j' \neq j\right)$ can be defined based on the Cosine similarity:

$$\mathrm{CosSim}\left(\mathbf{m}_j\right) = \frac{\sum_{j \neq j'} \mathrm{Bet}\left(\mathbf{m}_j\right) \mathrm{Bet}\left(\mathbf{m}_{j'}\right)}{\sqrt{\sum_{j} \mathrm{Bet}^2\left(\mathbf{m}_j\right)} \sqrt{\sum_{j'} \mathrm{Bet}^2\left(\mathbf{m}_{j'}\right)}} \tag{6}$$

Note that $\mathrm{CosSim}\left(\mathbf{m}_j\right)$ equals 0 when $\mathrm{Bet}\left(\mathbf{m}_j\right)$ and $\mathrm{Bet}\left(\mathbf{m}_{j'}\right)$ are orthogonal, i.e., two independent evidences are completely conflicting. On the contrary, $\mathrm{CosSim}\left(\mathbf{m}_j\right)$ approximates to 1 when $\mathrm{Bet}\left(\mathbf{m}_j\right)$ and $\mathrm{Bet}\left(\mathbf{m}_{j'}\right)$ are basically coincided, i.e., they offer the roughly same support on the given proposition. Then, we have the normalized Cosine ratio:

$$\mathrm{CosRat}\left(\mathbf{m}_j\right) = \frac{\mathrm{CosSim}\left(\mathbf{m}_j\right)}{\sum_{j} \mathrm{CosSim}\left(\mathbf{m}_j\right)} \tag{7}$$

We calculate the weight of $\mathbf{m}_j$ as follows:

$$w_j = \frac{\mathrm{CosRat}\left(\mathbf{m}_j\right)}{\max_{j}\left(\mathrm{CosRat}\left(\mathbf{m}_j\right)\right)} \tag{8}$$

At this time, $\mathbf{m}_j$ is for the BPA improvement. Recalling Equation (3), we update m_{ji} and φ_j using Equation (7):

$$m_{ji} \xleftarrow{\text{Update}} w_j m_{ji} \tag{9}$$

$$\varphi_j \xleftarrow{\text{Update}} w_j\left(\varphi_j - 1\right) + 1 \tag{10}$$

Note that w_j in the equations above weaken the uncertain and conflicting BPA m_{ji} and strengthen φ_j for eliminating some 0s. The equations reduce the impact of uncertain evidence on the communication and alleviate conflict among evidences.

B. COMBINATION IMPROVEMENT

Proposition 1: Assume that the improved BPA vector is $\mathbf{m}_j = \left[m_{j1} \cdots m_{js}\ \varphi_j\right]$ when $j \geq 2$, the combined BPA vector $\tilde{\mathbf{m}}_j = \left[\tilde{m}_{j1} \cdots \tilde{m}_{js}\ \tilde{\varphi}_j\right]$ can be defined by:

$$\begin{aligned} \tilde{\mathbf{m}}_j &= \mathbf{m}_j \oplus \mathbf{m}_{j-1} \oplus \cdots \oplus \mathbf{m}_1 \\ &\underset{\text{matrix formation}}{\overset{\text{matrix formation}}{\rightleftharpoons}} \left(\mathbf{m}_j^{\mathrm{T}} \tilde{\mathbf{m}}_{j-1}\right) K_j \end{aligned} \tag{11}$$

where the matrix computation is the sum of each element on the diagonal and its corresponding elements at the top-right and bottom-left corners (the latter computation involves only one element on the diagonal). On the contrary, the matrix formation separates the sum into three elements of the diagonal and corners iteratively. Further, some parameters are given by:

$$\tilde{m}_{ji} = \begin{cases} \prod_{j=1}^{n}\left(m_{ji} + \varphi_j\right) - \prod_{j=1}^{n} \varphi_j, & n \neq 1 \\ m_{1i}, & n = 1 \end{cases} \tag{12}$$

$$\tilde{\varphi}_j = \begin{cases} \prod_{j=1}^{n} \varphi_j, & n \neq 1 \\ \tilde{\varphi}_1 = \varphi_1, & n = 1 \end{cases} \tag{13}$$

$$K_j = \prod_{j=1}^{n}\left(1 - \sum_{\substack{i,i'=1 \\ i \neq i'}}^{s} m_{ji}\tilde{m}_{(j-1)i'}\right)^{-1} \tag{14}$$

where K_j is the normalized factor.

Proof: We have the combined BPA element when $n \geq 2$:

$$\begin{aligned} \tilde{m}_{ji} &= \prod_{j=1}^{n}\left(m_{ji} + \varphi_j\right) - \prod_{j=1}^{n} \varphi_j \\ &= \left(m_{ji} + \varphi_j\right)\left(\tilde{m}_{(j-1)i} + \tilde{\varphi}_{j-1}\right) - \varphi_j\tilde{\varphi}_{j-1} \\ &= m_{ji}\tilde{m}_{(j-1)i} + m_{ji}\tilde{\varphi}_{j-1} + \varphi_j\tilde{m}_{(j-1)i} \end{aligned} \tag{15}$$

Note that $\tilde{m}_{ji}$ can be rewritten into the iteration form in Equation (15), that is, it equals to the sum of associated BPA product. According to the evidence combination rule, there is the basic element $\left(1 - C_j\right)^{-1}$, and K_j obeys the continued multiplication. We have in hand K_j Equation (14).

Let $(\cdot)^{\mathrm{T}}$ denote transpose matrix, $\tilde{m}_{ji}$ can be rewritten using Equation (12):

$$\begin{aligned}
\tilde{\mathbf{m}}_j &= \begin{bmatrix} \tilde{m}_{j1} & \cdots & \tilde{m}_{js} & \tilde{\varphi}_j \end{bmatrix} \left(1 - \sum_{\substack{i,i'=1\\ i\neq i'}}^{s} m_{ni}\tilde{m}_{(n-1)i'}\right)^{-1} \\
&\quad \times \prod_{j=1}^{n-1} \left(1 - \sum_{\substack{i,i'=1\\ i\neq i'}}^{s} m_{ji}\tilde{m}_{(j-1)i'}\right)^{-1} \\
&= \begin{bmatrix} m_{j1}\tilde{m}_{(j-1)1} + m_{j1}\tilde{\varphi}_{j-1} + \varphi_j\tilde{m}_{(j-1)1} \\ \vdots \\ m_{js}\tilde{m}_{(j-1)s} + m_{js}\tilde{\varphi}_{j-1} + \varphi_j\tilde{m}_{(j-1)s} \\ \varphi_j\tilde{\varphi}_{j-1} \end{bmatrix}^{\mathrm{T}} \\
&\quad \times \prod_{j=1}^{n} \left(1 - \sum_{\substack{i,i'=1\\ i\neq i'}}^{s} m_{ji}\tilde{m}_{(j-1)i'}\right)^{-1} \\
&\underset{\text{matrix computation}}{\overset{\text{matrix formation}}{\rightleftharpoons}} \begin{bmatrix} m_{j1}\tilde{m}_{(j-1)1} & \cdots & m_{j1}\tilde{m}_{(j-1)s} & m_{j1}\tilde{\varphi}_{j-1} \\ \vdots & \ddots & \vdots & \vdots \\ m_{js}\tilde{m}_{(j-1)1} & \cdots & m_{js}\tilde{m}_{(j-1)s} & m_{js}\tilde{\varphi}_{j-1} \\ \varphi_j\tilde{m}_{(j-1)1} & \cdots & \varphi_j\tilde{m}_{(j-1)s} & \varphi_j\tilde{\varphi}_{j-1} \end{bmatrix} \\
&\quad \times \prod_{j=1}^{n} \left(1 - \sum_{\substack{i,i'=1\\ i\neq i'}}^{s} m_{ji}\tilde{m}_{(j-1)i'}\right)^{-1} \\
&= \begin{bmatrix} m_{j1} & \cdots & m_{js} & \varphi_j \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \tilde{m}_{(j-1)1} & \cdots & \tilde{m}_{(j-1)s} & \tilde{\varphi}_{(j-1)} \end{bmatrix} \\
&\quad \times \prod_{j=1}^{n} \left(1 - \sum_{\substack{i,i'=1\\ i\neq i'}}^{s} m_{ji}\tilde{m}_{(j-1)i'}\right)^{-1} \\
&= \mathbf{m}_j^{\mathrm{T}}\tilde{\mathbf{m}}_{j-1}K_j \\
&= \mathbf{m}_j \oplus \mathbf{m}_{j-1} \oplus \cdots \oplus \mathbf{m}_1
\end{aligned} \tag{16}$$

Remark 2: In the proposed evidence combination rule, we replace the classic evidence combination under the matrix iteration computation so as to reduce the computational complexity. In the risk decision process, aiming at the overall size s of navigation risk set, at each time step index k, the computational complexity of the classic D-S evidence theory is $nO\left(2^{2s}\right)$. Then, the computational complexity in the available τ $(\tau \geq k)$ scans equals $n\tau O\left(2^{2s}\right)$. For comparison, the improved D-S evidence theory at each time step has the computational complexity in Table 1. When we only consider the iteration number of multiplication, the complexity of decision process is transformed from the power type into the quadratic type. Then, we have in hand the following equation when $s \geq 4$.

$$n\tau O\left(2^{2s}\right) > n\tau O\left(2s^2 + 5s + 2\right) \tag{17}$$

TABLE 1. Computational complexity of decision process.

No.	Computation	Complexity
1	$\mathbf{m}_j^{\mathrm{T}}\tilde{\mathbf{m}}_{j-1}$	$nO\left((s+1)^2\right)$
2	K_j	$nO(s)$
3	$\mathbf{m}_j^{\mathrm{T}}\tilde{\mathbf{m}}_{j-1}K_j$	$nO\left((s+1)^2\right)$
Total in τ scans		$n\tau O\left(2s^2+5s+2\right)$

C. RISK FORECASTING

As a warning of future navigation state, it has significance to make the moving transportations free from the potential hazard in complex navigation environment. At time step index $k-1$, we rewrite the posterior maximal BPA as $m_j(k-1|k-1)$ with the subscript j. Then, the BPA is forecasted by:

$$\begin{cases} m_j(k|k-1) = m_j(k-1|k-1) + \dot{m}_j(k-1|k-1)\,T \\ \dot{m}_j(k|k-1) = \dot{m}_j(k-1|k-1) \end{cases} \tag{18}$$

where T is the sampling time, and $\dot{m}_j$ denotes the instantaneous change rate of m_j.

Subsequently, the BPA is updated at time step index k:

$$\begin{cases} m_j(k|k) = m_j(k|k-1) + \alpha(k)\left(m_j(k) - m_j(k|k-1)\right) \\ \dot{m}_j(k|k) = \dot{m}_j(k|k-1) + \dfrac{\beta(k)}{T}\left(m_j(k) - m_j(k|k-1)\right) \end{cases} \tag{19}$$

where the filtering coefficients $\alpha(k)$ and $\beta(k)$ are:

$$\alpha(k) = \frac{2(2k-1)}{k(k+1)} \tag{20}$$

$$\beta(k) = \frac{6}{k(k+1)} \tag{21}$$

Remark 3: Note that $\alpha(k)$ and $\beta(k)$ gradually decreases with the increasing time step index k. They approximate to 0 when k tends to the infinity. If the involved BPA change is rapid, the random maneuver cannot be accurately defined, and then the existing α-β filter cannot forecast the reliable navigation risk. For this reason, the proposed α-β filter explores the adaptive filtering coefficients when the combined BPA becomes maneuvering.

First, we redefine $\beta(k)$ as follows:

$$\begin{aligned}
\beta(k) &= 2(2-\alpha(k)) - 4\sqrt{1-\alpha(k)} \\
&= 2\left(1 - \sqrt{1-\alpha(k)}\right)^2 \\
&= 2\left(1 - \sqrt{\frac{(k-1)(k-2)}{k(k+1)}}\right)^2
\end{aligned} \tag{22}$$

It is easy to prove that $\beta(k)$ becomes convergent when $k \geq 3$, which means the proposed α-β filter begins to stably operate at the 3rd time step.

Define the relative error between the combined BPA and the updated BPA at time step index k:

$$\Delta m_j(k) = \left| m_j(k) - m_j(k|k) \right| \tag{23}$$

Considering the standard deviation σ in the proposed filter, we have the other adaptive filtering coefficient:

$$\rho(k) = \sqrt{\alpha(k)} \tag{24}$$

Further, $\rho(k)\sigma$ represents the error of updated BPA and $\frac{\Delta m_j(k)}{\rho(k)\sigma}$ denotes the error ratio related to updated BPA. Let ε be the instability threshold, the time step index can be updated as:

$$k+1 \leftarrow \begin{cases} k - \text{round}\left(\left(\dfrac{\Delta m_j(k)}{\rho(k)\sigma} - \varepsilon\right)k\right), & \dfrac{\Delta m_j(k)}{\rho(k)\sigma} - \varepsilon > 0 \\ k+1, & \text{else} \end{cases} \tag{25}$$

where k is updated when the error ratio is more than the instability threshold. At this time, the maneuver of BPA is greater and k keeps decreasing. Otherwise, k automatically increases 1 in order to represent the stable BPA. Once k is updated, we will calculate the values of $\alpha(k)$, $\beta(k)$ and $\rho(k)$. We also need the counter τ to accumulate k when using Equation (25). In the navigation risk forecasting process, we select the posterior maximal BPA. The reason is explained that there are many elements in a combined BPA vector. However, the associated navigation risk level must be changed when the value is not maximal. At this time, j should be automatically selected by looking for the maximum when the BPA keeps decreasing. We set the threshold of $m_j(k|k)$ to 0.5. Once the navigation risk level is adjusted, the k will be taken from the beginning value 1. When the posterior maximal BPA is always less than 0.5, we have to check j at each time step.

$$j = \begin{cases} j, & m_j(k|k) \geq 0.500 \\ \sup\left\{\max\left\{m_j(k|k)\right\}\right\}, & m_j(k|k) < 0.500 \end{cases} \tag{26}$$

Remark 4: The proposed α-β filter inevitably needs extra computational complexity in Table 2 (only considering the iteration number of multiplication). Recalling the filtering framework, we use Equations (20), (22) and (24) to calculate the adaptive filtering coefficients, and use Equation (18) to forecast the navigation risk for the next time step. The computational complexity of the equations should be further considered. Note that the complexity is increasing with k. Once the order is reset, k will be recounted. With respect to τ in the counter, the complexity will not accumulate until the overall surveillance time is over. Then, we have the following equation when $s \geq 4$.

$$\tau O\left(s^3\right) > \tau O(11s) \tag{27}$$

TABLE 2. **Computational complexity of forecasting process.**

No.	Computation	Complexity
1	$\alpha(k)$	$O(2s)$
2	$\beta(k)$	$O(3s)$
3	$\alpha(k)\left(m_j(k)-m_j(k\mid k)\right)$	$O(s)$
4	$\beta(k)\left(m_j(k)-m_j(k\mid k)\right)$	$O(s)$
5	$\rho(k)$	$O(s)$
6	$\dfrac{\Delta m_j(k)}{\rho(k)\sigma}$	$O(2s)$
7	$\left(\dfrac{\Delta m_j(k)}{\rho(k)\sigma}-\varepsilon\right)k$	$O(s)$ at most
	Total in τ scans	$\tau O(11s)$

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. DECISION EXPERIMENT

In the numerical study, we used a scenario to assess the overall performance of the proposed approach. The experimental environment was: Intel$^{\text{TM}}$ Core$^{\text{TM}}$ i5, 8 GB memory and MATLAB$^{\text{TM}}$ R2018a. We employ four kinds of typical evidences, and the trivial, tolerable, moderate, substantial and intolerable risk levels.

To deal with the uncertain evidences, the uncertain level is also used. Among our tested datasets, we select a typical set of raw BPAs in order to analyze the decision performance. Then, the BPAs are presented in the matrix:

$$\mathbf{m} = \begin{bmatrix} 0.6500 & 0.2500 & 0.1000 & 0.0000 & 0.0000 & 0.0000 \\ 0.2000 & 0.2500 & 0.3500 & 0.1000 & 0.1000 & 0.1000 \\ 0.1000 & 0.2000 & 0.4500 & 0.1500 & 0.1500 & 0.0000 \\ 0.2000 & 0.3500 & 0.3000 & 0.0000 & 0.0000 & 0.1500 \end{bmatrix} \tag{28}$$

where the columns from left to right mean the trivial, tolerable, moderate, substantial, intolerable and uncertain risk levels. The rows from top to bottom mean the different evidences. The element in this matrix is the associated BPA. There are the conflicting BPAs in the first three columns owing to the maximal value in each row. For the classic D-S evidence combination rule, we have the combined BPAs:

$$\tilde{\mathbf{m}}_j = \left[0.2110 \quad 0.4057 \quad 0.3834 \quad 0.0000 \quad 0.0000 \quad 0.0000\right]^{\text{T}} \tag{29}$$

Note that in the first three columns, the combined BPA corresponding to the tolerable and moderate risk levels are roughly similar. The product of inconsistent BPA is

$$C_j = 0.9877 \tag{30}$$

where the value approximates to 1, which means there is the high conflict among the evidences. We cannot directly make reliable decision for this situation.

To overcome the difficulty above, we use the improved approach to calculate $\mathrm{Bet}\left(\mathbf{m}_j\right)$ related to Equation (28):

$$\mathrm{Bet}\left(\mathbf{m}_j\right) = \begin{bmatrix} 0.2000 & 0.2222 & 0.2000 & 0.2353 \end{bmatrix}^{\mathrm{T}} \tag{31}$$

Then, the Cosine similarity is given by:

$$\mathrm{CosSim}\left(\mathbf{m}_j\right) = \begin{bmatrix} 0.7118 & 0.7642 & 0.7118 & 0.7925 \end{bmatrix}^{\mathrm{T}} \tag{32}$$

The Cosine ratio is:

$$\mathrm{CosRat}\left(\mathbf{m}_j\right) = \begin{bmatrix} 0.2388 & 0.2564 & 0.2388 & 0.2659 \end{bmatrix}^{\mathrm{T}} \tag{33}$$

By using the weight of BPA,

$$w_j = \begin{bmatrix} 0.8982 & 0.9643 & 0.8982 & 1.0000 \end{bmatrix}^{\mathrm{T}} \tag{34}$$

the optimized BPA matrix can be written as:

$$\mathbf{m} = \begin{bmatrix} 0.5838 & 0.2246 & 0.0898 & 0.0500 & 0.0500 & 0.1018 \\ 0.1929 & 0.2411 & 0.2875 & 0.0964 & 0.0500 & 0.1321 \\ 0.0898 & 0.1796 & 0.4042 & 0.1347 & 0.0898 & 0.1018 \\ 0.2000 & 0.2500 & 0.3000 & 0.0500 & 0.0500 & 0.1500 \end{bmatrix} \tag{35}$$

Comparison with Equation (28), there is no 0s in Equation (35) and each BPA has weighted. Finally, the combined BPAs under the proposed combination rule are:

$$\tilde{\mathbf{m}}_j = \begin{bmatrix} 0.2233 & 0.3239 & 0.4171 & 0.0043 & 0.0015 & 0.0274 \end{bmatrix}^{\mathrm{T}} \tag{36}$$

Note that the moderate risk level is maximal, and others are lower than 1/3 that is a usual constant value in practical engineering. Comparison with Equation (29), the current decision of moderate risk level is reliable.

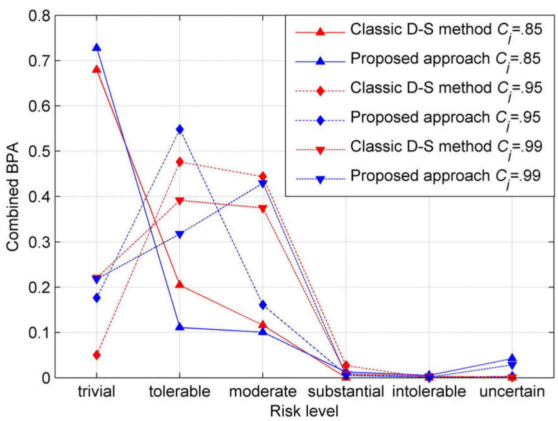


FIGURE 1. Decision result of different methods.

Figure 1 shows the combined BPA of two kinds of approaches under the different C_j. Note that the decision result becomes more instable when C_j is increasing in the classic D-S evidence theory method. The reason is explained that some available evidences lead to conflicting BPAs. Besides, the classic method cannot obviously distinguish between tolerable level and moderate level because the BPAs are more approximate. By comparison, the proposed approach makes satisfactory decision whether the conflict is higher or lower. For example, we achieve the current risk level is moderate when C_j is 0.990. Of course, the final result is in line with the ground truth.

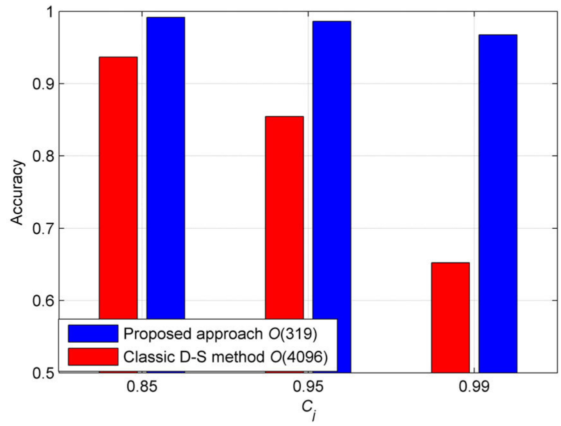


FIGURE 2. Decision accuracy of different methods.

Figure 2 shows the comparison result of the classic D-S met and the proposed approach. Note that the proposed approach has the higher accuracy under the different C_j. Some uncertain evidences are corrected based on the weighted BPA. Further, the Cosine ratio makes significant role in the decision process. There is a remarkable improvement under the condition of $C_j = 0.990$. Moreover, the computational complexity of the proposed approach is 7.8% of the classic D-S method. As for the classic method, it is hard to construct a more reasonable BPA when the evidence combination rule is directly used.

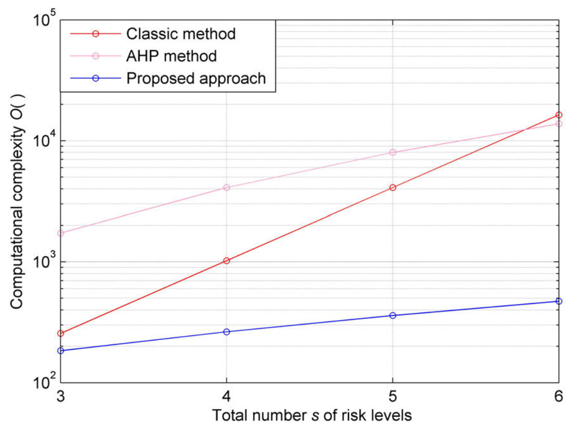
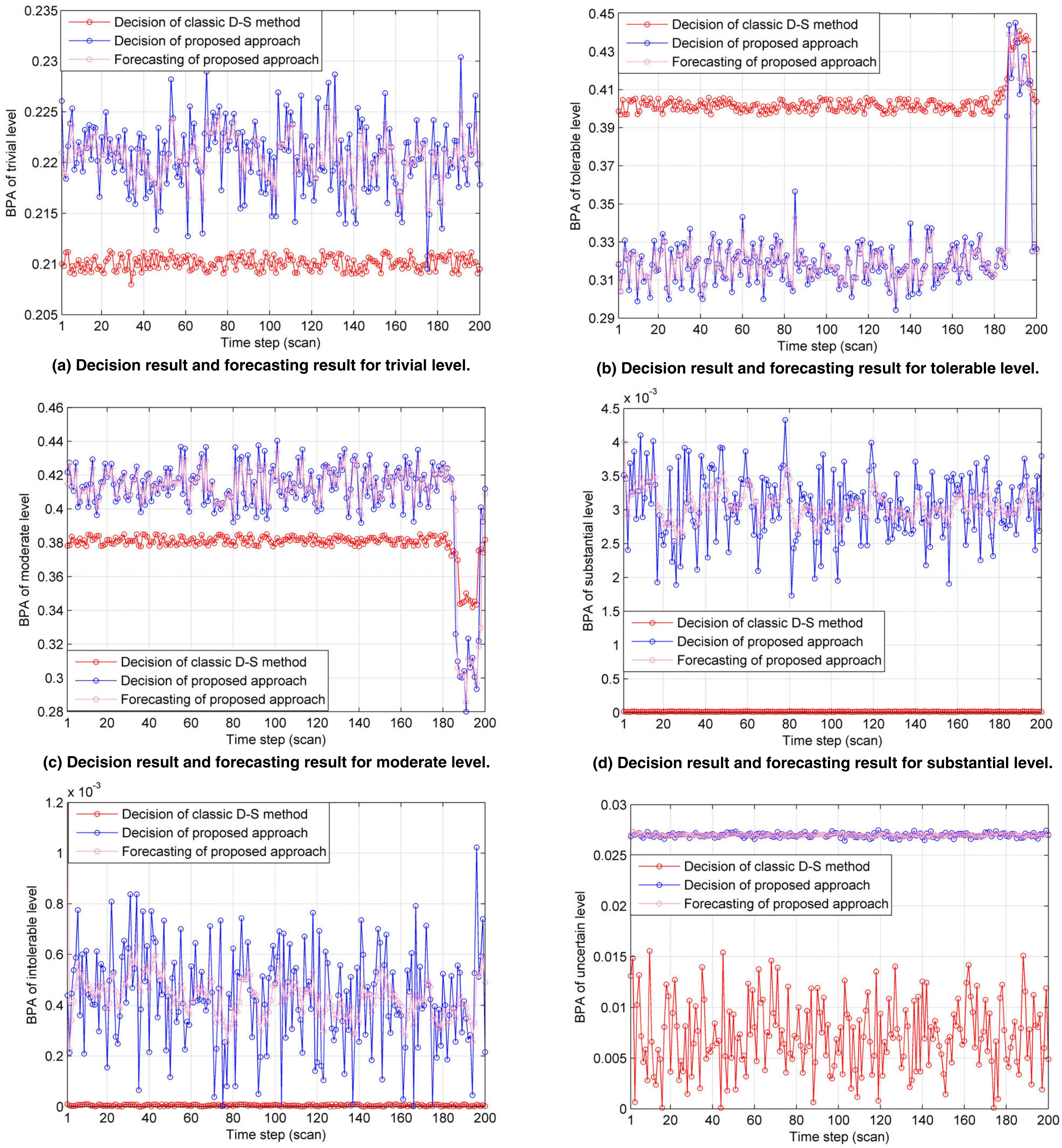


FIGURE 3. Decision accuracy of different methods.

Figure 3 compares the computational complexity using three methods under the different s. We make change s from 3 to 6 for simplicity. The proposed approach including the process of the BPA computation has the smallest fluctuation against other two methods with the increasing s. For the popular AHP method, we need the eigenvalue of the high-order



(a) Decision result and forecasting result for trivial level.

(b) Decision result and forecasting result for tolerable level.

(c) Decision result and forecasting result for moderate level.

(d) Decision result and forecasting result for substantial level.

(e) Decision result and forecasting result for intolerable level.

(f) Decision result and forecasting result for uncertain level.

FIGURE 4. Decision result and forecasting result.

matrix when getting the consistency ratio in the decision process, where the computational complexity of eigenvalue is proportional to the cubic of s. Although it is regarded a popular method on the navigation risk decision, compared with D-S method, the AHP method still has the highest complexity in the case of $s \geq 6$.

B. FORECASTING EXPERIMENT

Figure 4 compares the decision result and forecasting result using two methods during continuous 200 scans. We make use of the BPA decision value on the certain risk level j in the proposed approach as $m_j(k)$ at the time step k. After some statistical analysis, we set the related parameters $\sigma = 0.010$ and $\varepsilon = 0.950$ for achieving better forecasting performance. Note that the forecasting result on each risk level approximates to the decision result in the proposed approach. It can be explained that the proposed α-β filter provides the reliable forecasting result. Since the BPA fluctuation is dominated by the uncertain and conflicting evidences, the proposed filter adjusts forecasting when the available evidence changes. We can easily make the decision during the surveillance period. For the most time before the 185$^{\text{th}}$ scan, we find that the forecasting result on the moderate level are mainly dominant, which changes around the average value 0.417. The tolerable level has the greater value in the proposed approach and its average value is about 0.320. It represents the BPA change rapidly from the 185th scan to the 200th scan. Of course, the uncertain level is acceptable. It can also be verified that the proposed filter gives the satisfactory forecasting for various evidences. Suppose that $m_j(k)$ is given by the decision of proposed D-S method, the proposed α-β filter can be executed with the initial values. As a result, there are small error permutations from the decision of the proposed D-S method because of the improved filtering mechanism. Although the timely navigation risk assessment is necessary, the risk forecasting is of significance in the navigation engineering. We can make stable decision using the proposed approach. By comparison, the classic D-S method cannot make the accurate decision because the difference between the moderate level and the tolerable level is not remarkable.

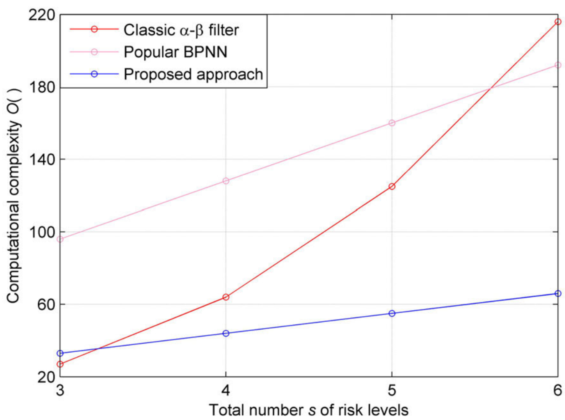


FIGURE 5. Comparison of decision and forecasting.

Subsequently, we analyze the computational complexity of the classic α-β filter, popular BPNN and proposed approach. Figure 5 indicates the averaged complexity under the different s. Note that the computational complexity of forecasting risk of the proposed method is the lowest owing to the individual filtering framework for each risk level in the low-dimension space, but not in the entire-dimension space. For the BPNN (3-input-layer, 8-hidden-layer and 3-output-layer), it linearly increases and then approximates the product of s and the number of nodes in the hidden layer (8 nodes). In the classic method, it has the greatest value when $s > 6$.

C. PRACTICAL EXPERIMENT

There are two kinds of practical experiments in this section. First, in view to the actual maritime engineering, the dominant evidences of water traffic contain four categories: the hydrological evidence, meteorological evidence, environmental evidence and navigable evidence. Corresponding to

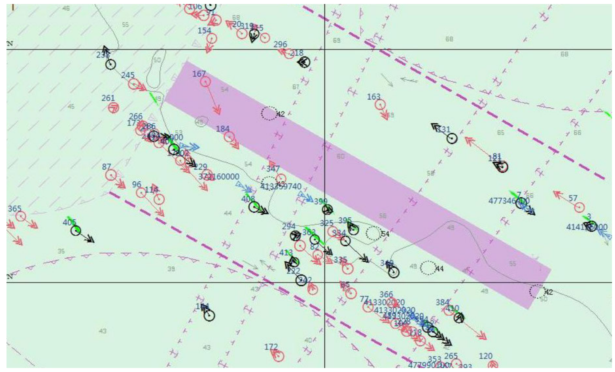


FIGURE 6. For actual maritime engineering.

Figure 6, we have in hand the following BPA matrix:

$$\mathbf{m} = \begin{bmatrix} 0.1000 & 0.1000 & 0.7000 & 0.0500 & 0.0000 & 0.0500 \\ 0.2000 & 0.5000 & 0.1000 & 0.1000 & 0.1000 & 0.0000 \\ 0.1000 & 0.1000 & 0.1000 & 0.6000 & 0.0500 & 0.0500 \\ 0.6000 & 0.0000 & 0.2000 & 0.1000 & 0.0000 & 0.1000 \end{bmatrix} \tag{37}$$

where each evidence has different maximal BPA related to the evidences from the upper row to the lower row. For example, we find that the hydrological evidence has the BPA of 0.7000 for the moderate level.

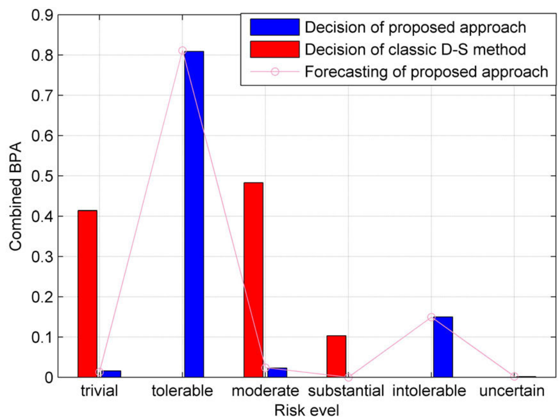


FIGURE 7. Decision and forecasting result corresponding to Figure 6.

Figure 7 demonstrates the decision and forecasting result. The BPAs of trivial and moderate risks are approximated in the current environment. For the proposed approach, it presents the maximal BPA of 0.813 for the tolerable level. The forecasting result coincides with the stable decision. It provides the reliable information with the smaller error covariance.

For the actual traffic engineering in Figure 8, we think of the weather evidence, road facility evidence, vehicle evidence and pedestrian evidence. Although the road facility is relatively stable, the weather evidence from climate sensors is tender. The pedestrian dynamics maybe have random

FIGURE 8. For actual traffic engineering.

motion characteristics. In Figure 8, we have the following BPA matrix:

$$\mathbf{m} = \begin{bmatrix} 0.6500 & 0.2500 & 0.1000 & 0.0000 & 0.0000 & 0.0000 \\ 0.2000 & 0.2500 & 0.3500 & 0.1000 & 0.1000 & 0.1000 \\ 0.1000 & 0.2000 & 0.4500 & 0.1500 & 0.1500 & 0.0000 \\ 0.2000 & 0.3500 & 0.3000 & 0.0000 & 0.0000 & 0.1500 \end{bmatrix} \tag{38}$$

Similarly, we achieve the decision and forecasting result using the proposed approach in Figure 9. Note that the weather is fine and other evidences are tolerable or moderate. There are some 0s in the equation above. Therefore, the classic D-S method cannot complete risk decision based on the original evidences, and then gives ineffective values. The proposed approach can provide the decision and forecasting results of trivial level.

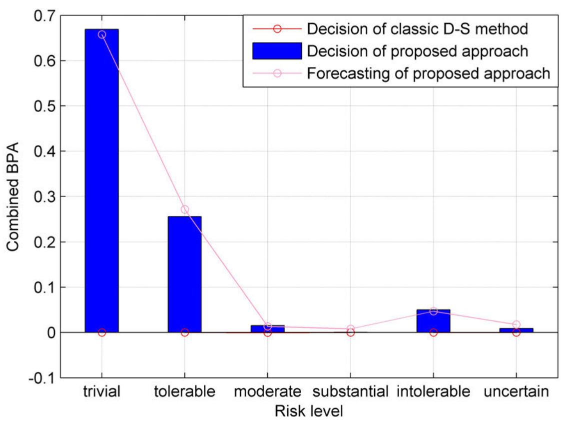


FIGURE 9. Decision and forecasting results corresponding to Figure 8.

According to the practical experiments, the reliability of the proposed approach is enhanced in two aspects: the BPA weight is used to weaken the uncertainty and conflict in the decision process. Moreover, the novel filtering mechanism optimizes the coefficients to overcome the BPA maneuvers in the forecasting process. With respect to the efficiency, the complexity of decision process becomes the quadratic type based on the matrix operation. Besides, the complexity is also reduced because the adaptive filtering coefficients and the number of scans are both considered.

V. CONCLUSION

The primary challenges are to deal with the unstable performance of the existing methods on the navigation risk assessment. This study presents an innovative decision and forecasting approach. We first analyze the classic D-S evidence theory as a typical assessment method. Regarding on its disadvantages, we weight the BPAs and utilize the Cosine ratio to overcome the uncertainty of BPA. Afterwards, the evidence combination rule is explored based on the matrix formation and computation for lower complexity. Considering the forecasting performance, the adaptive α-β filter is developed in the filtering framework. Also, we discuss the computational complexity individually. The numerical studies and actual experiments demonstrate that the intelligent decision and forecasting can be achieved with the satisfactory performance for navigation risk assessment in both maritime and traffic engineering. In our work, although the BPA computation is suitable for the uncertain and conflicting evidences, the extra complexity has been involved. Once the number of current evidences exploded, the complexity will be affected. Therefore, as for the next research developments, we will further improve the assessment efficiency of the proposed approach.

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